Direction Interval Retrieval With Thresholded Nudging: A Method For Improving The Accuracy of QuikSCAT Winds

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Abstract— The SeaWinds on QuikSCAT scatterometer (QSCAT) was developed by NASA JPL to measure the speed and direction of ocean surface winds. The accuracy of the majority of the swath, and the size of the swath are such that QSCAT meets its science requirements despite shortcomings at certain cross track positions. Nonetheless, it was desirable to modify the baseline processing in order to improve the quality of the less accurate portions of the swath, in particular near the far swath and nadir. Two disparate problems have been identified for far swath and nadir. At far swath, ambiguity removal skill is degraded due to the absence of inner beam measurements, limited azimuth diversity, and boundary effects. Near nadir, due to nonoptimal measurement geometry, (measurement azimuths approximately 180° apart) there is a marked decrease in directional accuracy even when ambiguity removal works correctly. Two algorithms were developed, direction interval retrieval (DIR) to address the nadir performance issue, and thresholded nudging (TN) to improve ambiguity removal at far swath.

We illustrate the impact of the two techniques by exhibiting post-launch statistical performance metrics with respect to *European Center for Medium-range Weather Forecasting* (ECMWF) wind fields.

INTRODUCTION

Before discussing the new algorithms in detail, we first review some of the general theory of wind scatterometers as well as some features peculiar to the QSCAT instrument. A scatterometer is a microwave radar which measures the normalized backscatter cross section, σ_0. Geophysical model functions (GMF) have been developed empirically which map ocean wind speed and direction to σ_0 [1, 2, 3]. The theoretical basis of this relationship is the action of wind on small-scale (capillary) ocean surface waves, which in turn effect the ocean surface backscatter [4].

A single σ_0 value may have been produced by a number of different wind vectors. Multiple measurements from different look geometries are required in order to uniquely determine a wind vector. The QSCAT scatterometer employs two conically scanning antenna beams. The two beams differ in incidence angle (46°, inner beam; 54°, outer beam) and polarization (H pol, inner beam; V pol, outer beam). For most of the swath, every 25 km by 25 km cell on the ground is measured using four different look geometry configurations. Fore and aft measurements are obtained for each beam.

The viewing geometry differs across the swath. For the outer portions the swath, the viewing geometry is suboptimal: no inner beam measurements are available, and as the extreme edge of the swath is approached, the azimuth diversity of the measurements approaches zero. At nadir, both beams are available, but the antenna azimuths are nearly 180 degrees apart between fore and aft looks. For more detailed discussion of the QSCAT instrument see [5].

ALGORITHM

Direction Interval Retrieval

For QSCAT the rate at which the likelihood value drops off from the maxima varies with cross track distance. For wind vector cells near nadir, there are large ranges of direction over which the likelihood value is relatively similar, and it is inaccurate to represent the set of likely wind vectors by the likelihood maxima alone. The DIR method addresses this problem by calculating a solution set for each wind vector cell which includes a range of wind directions around each likelihood maxima. The extent of the ranges is determined independently for each wind vector cell according to the specific shape of the likelihood function for that cell.

The DIR technique is a set theoretic estimation technique [6] which incorporates information from the σ_0 measurements and a model of the noise on those measurements in order to construct the solution set. Allowing the technique to consider all possible sets of wind vectors would be time prohibitive, so a simplifying assumption must be made regarding the types of sets to be considered. For each wind direction ϕ there is a wind speed $u(\phi)$ which maximizes the likelihood function. We refer to the curve thus defined as the best speed ridge. In the baseline technique, solution sets are four or fewer points on the best speed ridge corresponding to local likelihood maxima. In DIR, solution sets are generalized to four or fewer segments of the best speed ridge, with each segment including a local maxima. This choice of solution set is justified by the observations that likelihood drops off sharply for

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speeds away from the best speed ridge, and that whenever the wind direction is determined accurately the wind speed is as well.

The endpoints of the segments are determined by estimating error bounds in a manner similar to techniques described in [7]. These techniques estimate probability distributions (and confidence intervals) for each measurement then combine information by intersecting solution sets derived from confidence intervals on each measurement. The DIR technique instead estimates a joint probability distribution for all the measurements and then directly computes the solution set, yielding a more accurate result. Such a technique is seldom employed due to computational efficiency concerns, but since most of the information needed for the calculation is already available from the maximum likelihood estimator and the search space is limited to one dimension (by the best speed ridge assumption) efficiency is not a problem.

We assume the noise on the measurements is mutually independent and Gaussian. The means and variance of the Gaussian noise used in the maximum likelihood estimator can be used to compute the conditional probability density of obtaining the σ_0 measurements given a wind vector represented by speed and direction (u, ϕ), $P(\{\sigma_{0i}\}|u, \phi)$. In fact the conditional probability is related to the likelihood estimate $f(u, \phi)$ by:

$$P(\{\sigma_{0i}\}|u, \phi) = k \exp(f(u, \phi)/2) \tag{1}$$

for some constant k. By assuming the prior wind speed and direction probabilities are uniform, Bayes' theorem can be used to estimate the conditional probability density of wind solutions given the measurements. In order to simplify the processing we normalize so that the probability that the wind solution falls on the best speed ridge is one.

Once the estimation of the probability density function (pdf) has been obtained, the solution set segments are determined by thresholding the probability. Given a threshold T, a set of directional intervals around each of the local maxima is selected such that the sum of the widths of the intervals is minimized and the integral of the pdf over the intervals is T. From simulation, the choice of $T = 0.8$ was found to be *reasonable*.

Once the solution set has been calculated for each wind vector. Ambiguity removal is performed to select a unique solution vector from each solution set. A two step procedure is employed. First one of the disjoint segments which composes each solution set is selected by performing ambiguity removal in the usual manner [1]. Ambiguity removal is performed on the local likelihood maximas and the segment which encloses the selected maxima is chosen. Next, a unique vector within the chosen segment is selected by iteratively choosing the vector which is closest in direction to the median vector of the surrounding 7 x 7 window.[2] Each wind vector cell is initialized by the maxima within the selected segment. Wind vectors are not updated until after each median filtering pass is complete. Passes continue until no wind vectors change by more than a threshold amount (5 degrees) or a maximum number of passes (100) is exceeded.

Thresholded Nudging

The baseline nudging algorithm, which is identical to the NSCAT algorithm, chooses an ambiguity to initialize the median filter. The number of ambiguities available for initialization must be limited in order to minimize the influence of the nudging field, and to use as much scatterometer information as possible. If all ambiguities are allowed to be selected by the nudging field, the retrieved wind field would be very close to the nudged wind field, defeating the point of making the measurement. Currently, that algorithm only allows one of the two most likely ambiguities to be chosen. The rationale for that limit is based on NSCAT experience: we assume that the scatterometer can choose the correct streamline, and want the nudging field to select the proper ambiguity from that line.

The QSCAT situation is quite different from the NSCAT situation. In the outer swath, the scatterometer can not always select the correct streamline. A significant percentage of the time (10-15 percent in simulation) the ambiguity closest to the truth is the third or fourth ranked ambiguity. Given that situation, one method that suggests itself is to use more ambiguities for nudging in the outer swath.

The likelihood function can be converted into an estimate of probability. (see previous section) Using equation 1 we calculate *relative likelihood* a quantity proportional to $P(\{\sigma_{0i}\}|u, \phi)$ normalized so that the relative likelihood of the first ranked ambiguity is one. The method by which we set the maximum rank for nudging is based on choosing the number of ambiguities above a certain threshold, M in relative likelihood. The threshold itself should be a function of the quality of the nudge field. The value used to generate the results presented in this paper, $M = 0.2$, was determined via simulation. Wind performance was found to be relatively insensitive to this value (in simulation) with values of .1 and .3 yielding similar performance.

RESULTS

Comparisons to ECMWF

In this section we compare QSCAT retrieved winds using both the baseline and DIRTH techniques with ECMWF analysis wind fields. One degree by one degree ECMWF

[1] with the exception that the median filter is initialized using thresholded nudging. See next section for more detail.

[2] The window size was chosen to correspond to the size used by the baseline median filtering algorithm. Additional window sizes deserve further study both for DIR and the standard algorithm.

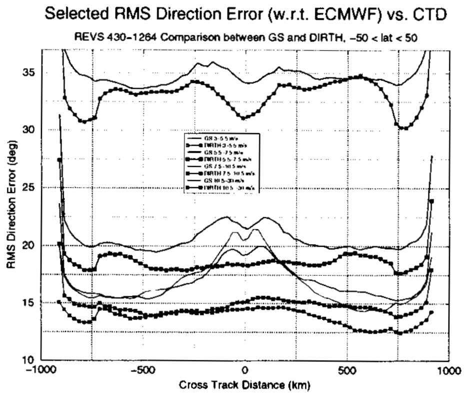

Figure 1:

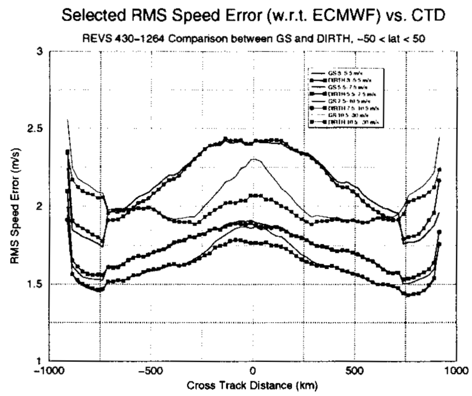

Figure 2:

wind fields were used and interpolated spatially (but not temporally) to the QSCAT wind vector cell locations. ECMWF wind fields are produced every six hours and each 90 minute QSCAT orbit was only co-located with a single ECMWF field, so that the greatest possible temporal difference is three hours and 45 minutes. When on occasion a particular ECMWF wind field was unavailable the orbits temporally co-located with that field were left out of the analysis. Figure 1 depicts the RMS direction difference between ECMWF and the retrieved winds for the baseline (GS) and DIRTH wind retrieval methods. The directional differences are plotted versus cross track distance for four ranges of ECMWF wind speeds. Figure 2 depicts the RMS speed differences similarly. High latitudes were left out in order to avoid problems with known errors in the QSCAT ice edge map. High latitudes do tend to have higher wind speeds, but since we break down the results by wind speed the impact of preferentially removing high speed cases is likely to be minimal.

DIRTH reduces the directional differences from ECMWF significantly across the entire swath for all ranges of wind speeds. The speed RMS difference values are similar for the baseline and DIRTH cases. The only substantial differences are a slight advantage for DIRTH in the mid swath region for the two highest wind speed ranges. There is also a small discrepancy in the far swath with a marginal advantage for DIRTH at the highest wind speed range, and a similarly marginal advantage for the baseline technique at lower wind speeds.

SUMMARY

In summary, the DIRTH method noticeably improves the QSCAT retrieved wind vector solutions, as evidenced by comparisons with ECMWF, and reduces the cross swath variation in wind vector accuracy. DIRTH solution vectors along with the baseline selected ambiguities are now available in the official QSCAT L2B product.

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